Synopsis of the PhD Thesis

Classification and Prediction of Stages of Kidney Health using Ultrasound Images

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1 ABSTRACT

When human kidney function deteriorates for three or more months with/without structural damage, this represents a disease known as chronic kidney disease (CKD). CKD poses serious threat to human life. CKD categorized into five stages (Stage-1, Stage-2, Stage-3, Stage-4, and Stage-5). These stages represent level of severity from mild (stage-1) to dangerous level (Stage-5). CKD progression can be controlled if detected at early stage. Clinically CKD identified through a test, known as glomerular filtration rate (GFR) test. This test uses patient's blood and urine sample for CKD stage determination. It has limitations such as invasive, expensive, time consuming etc. An automatic CKD stage detection system could overcome the limitations of clinical approach and help early detection of CKD stages.

This thesis work proposes novel computing schemes for identification of CKD stages with higher accuracy and estimation of nephron loss using ultrasound (US) kidney images. Literature review is presented in Chapter-2 to identify issues of existing computing schemes for CKD stage identification. A GLCM based computing scheme is proposed in Chapter-3 for CKD stage identification. The proposed scheme uses fourteen selected GLCM features and classify five CKD stages with more than 97% accuracy. A pattern matching scheme is proposed in Chapter-4 to estimate the amount of nephron loss in kidney internal parts. Image registration (IR) and structural similarity index (SSIM) algorithms are used to estimate the similarity index of different CKD images with respect to normal kidney image. Simulation result shows that, the proposed scheme using IR with translation transform estimates nephron loss from 30% to 34% in cortex region and from 46% to 58% in medulla region of kidney. Chapter-5 presents pattern matching scheme for CKD stage classification with an objective to develop a unified computing method for CKD stage identification and nephron loss. The proposed scheme uses a template instead of image features for classification of CKD stages. The template is developed using similarity index values for different CKD stages. Simulation results shows that template of IR with similarity transform can detects CKD stages with 96% accuracy. The proposed pattern matching based scheme has two fold advantages over the existing schemes. (i) It does not required image features and a multistage classifier for CKD stage classification. Instead of that, a simple template is used. (ii) It uses pattern matching scheme which also can be used for estimation of nephron-loss in kidney part. Chapter-6 presents computing scheme based on transfer learning (TL) models which is suitable for small sized data-set of CKD images.

Simulation result shows that the proposed scheme based on TL achieves more than 95% classification accuracy for CKD stage identification. Conclusions are presented in Chapter-7 and future scope in Chapter-8.

2 INTRODUCTION

Human kidney functions include blood filtration, regulation and maintenance of required level of nutrients in the body etc. The kidney functions performed in two regions: *cortex* and *medulla.* Another integral part of kidney is pelvis, which collects urine from cortex and medulla and pass it to ureter. Within the cortex and medulla lies the functional unit of the kidney known as *nephrons*. The number of nephron vary from approximately 200,000 to more than 2.5 million [1]. The nephron modulate pH and blood pressure [2]. When nephron works excessively, due to reasons such as hypertension, diabetic, inflammation of kidney etc. [3], upon normalization, nephrons fail to work normally as earlier and the filtering capability of kidney decreases. The decline in kidney function for three or more months, with/without structural damage to nephron, results into a disease, known as chronic kidney disease (CKD) [3]. CKD progression is irreversible and not felt by patient. CKD if left untreated, progresses towards end stage, which requires dialysis (artificial blood filtering mechanism) or kidney transplant. The global prevalence of CKD was >10% in the year 2022, amounting to approximately > 800 million individuals [4]. The global prevalence of CKD among the adults in: India 10.2% [4], Singapore 34.3% [4], Bangladesh 17.3% [4], Nigeria 12% [5], Belgium 4.4% [6], United Kingdom 6.5% [6], Iran 27.5% [7], Germany 17.3% [8], China 16.8% [8], and USA 5.7% [9].

The preferred test for identification of CKD is glomerular filtration rate (GFR) test. It is also known as blood-urine test [10]. The GFR test score mapped in different ranges for five CKD stages. A normal kidney filtering range is in $120 \sim 130\,\text{mL/min/1.73 m}^2$ value of GFR [10]. GFR values in the range of 90 ~ 119 illustrate CKD stage-1, 60 ~ 89 illustrate stage-2, 30 ~ 59 illustrate stage-3, 15 ~ 29 illustrate stage-4 and < 15 illustrate stage-5 [10]. CKD defined as low kidney function with GFR value <60 mL/min/1.73 m^2 for three or more months with/without damaged kidney [11]. GFR method of CKD detection suffers with drawbacks such as; sensitivity of GFR method is low for early stage detection [12]. GFR method uses sample of patient's urine for test. Collection time of urine and storage is a major factor which significantly alters the result [13]. GFR method is invasive, time consuming, expensive [14]. In few cases, the damaged nephrons remain undetected in GFR test and that results into quick progression of CKD silently which cannot be observed externally. An automatic system is considered for CKD stage detection which is non-invasive, not introduce any discomfort to patient, less time consuming and ease in acquisition of patient data.

The automatic systems use ultrasound kidney image of the patient which is easily obtained at low cost. Image processing algorithms are used to extract image features from the US kidney image and those image features are processed by the classifier for classification of CKD stages. Design of a computing scheme for identification of CKD stages with higher accuracy is an interesting research area.

The prime reasons for decline in kidney function is due to death of nephron cells which is a slow process. When nephron fails to function normally, the filtering capability of kidney decreases and that leading to CKD. Nephrons are found in the cortex and medulla of the kidney region. In other word, the CKD progression is directly linked with the progression in death of nephron cells which impacts kidney internal parts particularly cortex and medulla. Early detection of nephron loss will help the nephrologist to have first-hand information on the amount of damage to the kidney parts to access the whole kidney health and initiate the treatment procedure to slowdown the CKD progression to avoid further damage to kidney.

In recent years, medical imaging domain has generated enormous amount of medical image data [15]. Medical practitioners are relying heavily on human visual system for identifying the severity of disease from the image [16]. But, there are ethical and practical limitations of manual assessment such as: number of images assessed at a time, inter operator variability, attention span of human expert etc. [17]. Deep learning (DL) domain is found to be very much useful for medical practitioners in data analysis and interpretations [17]. DL has the capability of analyzing a huge amount of data at a time. Training a DL model is a vital step that mimic human intuition. DL models can adapt internal parameters during the training phase similar to a human visual system [18] and these models are work on rule-based diagnosis procedure which provides the necessary clarity of the problem to be solved through intuition. DL model requires a large amount of labelled medical image data of specific type for training the network. However, it is difficult to obtain large amount human kidney images of different CKD stages.

Transfer learning (TL) models are considered for classification of CKD stages. TL model uses pre-trained networks such as AlexNet, LeNet, VGGNet, ResNet, GoogLeNet, DenseNet, and XceptionNet etc. These networks were trained on the ImageNet dataset or some other datasets and they can be fine-tuned using the available images of the specified problem [19]. TL approach offers promising results with a lower error rate using small amount of new dataset on re-trained

network [20]. Design of a TL model for classification of CKD stages with high accuracy is also an interesting area of research.

3. RESEARCH OBJECTIVES

Design of a computing scheme for automatic identification of CKD stages is an interesting research area. Based on this, the proposed thesis has the following research objectives.

1. Design a computing scheme for CKD stage classification with higher accuracy.
2. Impact of CKD progression on kidney parts in terms of nephron loss.
3. Use of machine learning technique for classification of CKD stages.

4 LITERATURE REVIEW

During the last decade, many computing schemes have been proposed in the literature for identification CKD stages with higher accuracy. These developments are briefly discussed here to identify the issues in each of the identified research objectives.

4.1 CKD stage classification using image features

A scheme using geometrical features (standard deviation, area analysis, brightness analysis) and statistical features (entropy, contrast, homogeneity and angular second momentum) extracted from the US image and considered jointly in [14]. These image features when processed by SVM classifier with Gaussian kernel individual CKD stages identified with nearly 70% accuracy [14]. Another scheme proposed by [12] to distinguish between normal and CKD kidney images by estimating the kidney cortex area using GLCM features. *From the literatures, it has been identified that, the CKD stage group classification accuracy is low, and this group accuracy further decreased when individual stages identified. This mainly because of image features. A feature extraction scheme is require, which can extract and identify contributing features from source US kidney images. These contributing features will improve the group and individual classification accuracy.*

4.2 Estimation of nephron loss in kidney internal parts due to CKD progression

A method proposed in [21] for identification of kidney disease, such as cysts, tumors, stones, and the normal. A method proposed in [22], for detection of kidney stone and size of stone. A method proposed in [23], for classification of normal kidney image and presence of hydronephrosis. A scheme suggested in [24] for identification of congenital anomalies of the kidneys and urinary tract (CAKUT). Autosomal dominant polycystic kidney disease (ADPKD) is a kidney of disease which results into CKD stage-3, a method using kidney length for prediction of CKD stage-3 proposed in [25]. *In literature, there are many schemes are suggested to identify kidney disease, but a scheme require to identify the underline effect of these disease on kidney parts i.e. identification of nephron loss in cortex and medulla region. Estimation of nephron is an important aspect. A computing scheme is require, which can identify the nephron loss due to CKD progression in kidney internal parts.*

4.3 A unified computing scheme for CKD stage identification and estimation of nephron loss

Intensity histogram (IH) feature, Invariant moments (IM), GLCM, Gray level run length matrices (GLRLM) features extracted from US kidney image. These features processed alone as well as mixed in each other for classification of kidney image into normal and abnormal (cyst, CKD, renal calculus) state in [26]. A smartphone based kidney disease detection system proposed in [27]. It uses GLCM, GLRLM, IH features for identification of kidney images into normal and abnormal class. Many schemes are suggested to improve the CKD stage classification accuracy. *All these schemes use one algorithm for feature extraction, another for selection of contributing feature and one more algorithm for classification. A unified computing scheme is required which can use one algorithm to identify CKD stage as well as estimate nephron loss due to CKD progression from source US kidney image.*

4.4 Use of machine learning for classification of CKD stages.

A Texture branch network for classification in CKD and non-CKD from ultrasound images proposed in [28]. An optimized deep convolutional neural network (ODCNN) proposed for classification in CKD and non-CKD [29]. Another TL model named Auxiliary Classifier Wasserstein Generative Adversarial Network (ACWGAN) with gradient penalty and

MobileNetV2 used in [30]. ACWGAN used to create synthetic dataset of CKD images of four CKD stages and MobileNetV2 model used to identify the four CKD stages with accuracy 81.9%. A hybrid TL model comprising Denset201used for classification of kidney images into normal, cyst, tumor and stone [31]. *Because of scarcity of US kidney image dataset in public domain, CNN models tuned for binary classification (CKD and non-CKD). TL models overcome the requirement of large dataset. TL models tuned for small sized dataset for multiclass classification, but low classification accuracy achieved.*

5 CONTRIBUTION

5.1. Identification of CKD stages using image features (Thesis Chapter-3).

For design of multi-stage classification computing scheme to improve the classification accuracy of CKD stages, US kidney image dataset is not available in public domain. With the help of Dr. Kiran Patil (MD Radiology) and radiology center "Shivam Diagnostic, Jalgaon, Maharashtra", we have prepared our own CKD image dataset. Collection, sorting, labelling and segmentation of US kidney images were done with the help of radiologists at radiology center. From the literature review it has been identified that, features when precisely selected, can contribute in classification accuracy. GLCM features are found suitable due to US gray nature of kidney images. Hence, we have extracted 21 GLCM features from source kidney image and identified and selected 14 contributing features only. These 14 features helps in achieving improved stage wise accuracy. These selected 14 contributing GLCM features tested on various multiclass classifiers such as linear discriminant analysis, K- nearest neighbor, SVM with different kernels (linear and Gaussian). A computing scheme for multiclass classification developed, which is shown below.

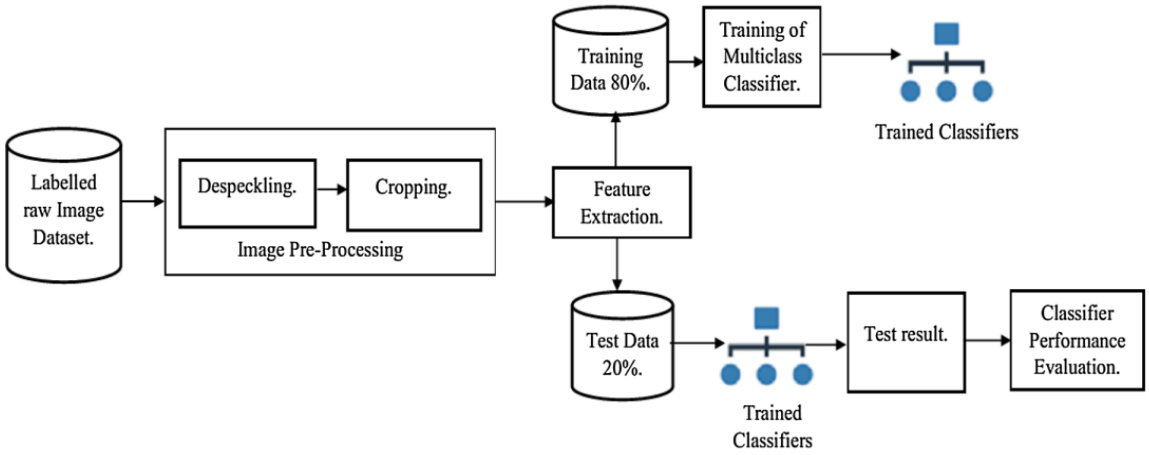

Figure-1: Block diagram of computing scheme for multiclass classification

Result and Discussion: Simulation results shows that the performance of LDA classifier is better than other multiclass classifiers. The LDA classifier processes the proposed 14 features to classify the US kidney images into stage-1, stage-3, stage-4, and stage-5 with marginally less than 100% accuracy and classify stage-2 with 100% accuracy.

5.2. Estimation of nephron loss in kidney internal parts due to CKD progression (Thesis Chapter-4).

For estimation of nephron loss in kidney parts (cortex and medulla), a dataset of segmented images of cortex and medulla regions prepared with the help of radiologist. A pattern matching scheme named, Image registration (IR) and structural similarity index (SSIM) algorithm for estimation of nephron loss identified. These two algorithms uses two images for matching, one image labelled as reference image and another image labelled as target image. A similarity value obtained from this matching. Similarity value 1 indicates complete match and value 0 indicates no match. Use of similarity index to measure the nephron loss in the kidney cortex and medulla regions, IR with different transform and SSIM algorithms used. One image of cortex region (labelled as reference image) from dataset of normal image (identified with the help of radiologist) compared with 30 images of cortex belongs to stage-1. Then same reference image of cortex compared with 30 images of cortex belongs to stage-2 and other stages. One image of medulla region (labelled as reference image) from normal image (identified with the help of radiologist) compared with 30 images of medulla belongs to stage-1. Then same reference image of medulla compared with 30 images of medulla belongs to stage-2.

Result and Discussion: In the cortex, the similarity value is almost 66%, which indicates almost 34% nephron loss due to CKD progression for stage-1 to stage-5. In the medulla, the similarity value is almost 49%, which indicates almost 51% nephron damage due to CKD progression for stage-1 to stage-5. IR using translation transform, identify nephron loss within range of 30% to 34% in cortex region and 46% to 58% in medulla region of kidney, which is in-line to clinical observations.

5.3. Template based approach for identification of CKD stage (Thesis Chapter-5).

A unified computing scheme is require which can identify CKD stage and nephron loss as well. This computing approach does not use feature extraction and classifier unlike the existing schemes. A template based approach for CKD stage classification developed. It uses a template instead of image features (and classifier) for CKD stage classification. In this scheme, whole kidney image is used. This scheme works in two steps. In step-1, it employs IR and SSIM algorithm for estimation of similarity index to develop the template/ reference-table for CKD stage classification. From image comparison disjoint range values obtained for different CKD stage. If these disjoint values used as a reference, during the testing of image, if the obtained similarity values falls in the gap, this will produce ambiguous result. Hence to avoid this, we used averaging method to obtain a clear range of values in step-1. In step-2, test images are compared for similarity value using IR and SSIM algorithm. The obtained similarity value mapped with the reference table developed in step-1, for stage identification. The block diagram of developed template based computing scheme is given below.

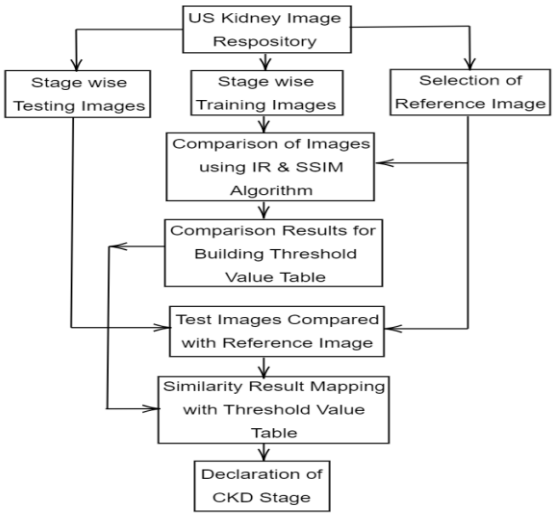
US Kidney Image Respository
Stage wise Testing Images
Stage wise Training Images
Selection of Reference Image
Comparison of Images using IR & SSIM Algorithm
Comparison Results for Building Threshold Value Table
Test Images Compared with Reference Image
Similarity Result Mapping with Threshold Value Table
Declaration of CKD Stage

Figure-2: template based method for identification of CKD stages.

Result and Discussion: Template based approach is simple and does not require separate algorithms for feature extraction and classification. The proposed template based approach, achieves almost 96% accuracy for stage-wise classification. A scheme proposed in [32] is the best among the existing computing methods, reported 97% accuracy for stage-wise classification. The stage-wise classification accuracy achieved through proposed template based approach is comparable with the scheme proposed in [32].

5.4. Machine Learning approach for identification of CKD stage (Thesis Chapter-6)

Neural networks (NN) tuned for classification of CKD stages. As these networks requires large amount of required data set for training and testing. Hence, researchers have tuned the networks for binary classification (for CKD and non-CKD).The scarcity of dataset can be overcome using transfer learning (TL) models. Initially TL models trained on very huge data set. Few layers of these pre-trained models requires re-training on available dataset (on which testing to be done). Then these re-trained models are tested on test images of available dataset. Recently researchers used TL model for CKD stage classification, but achieved low classification accuracy [30]. To achieve improved classification accuracy, selected and tuned TL models ResNet50, ShuffleNet80, MobileNet V2, VGG16, GoogleNet, and ResNet18for CKD stage classification.

Result and Discussion: Compared to other TL models, Resnet50 offers almost 95% classification accuracy. Compared to existing similar work [30] ResNet50 offers almost 13% higher classification accuracy for CKD stage wise detection and 13% higher aggregate accuracy.

6 Conclusion

CKD progression is irreversible and not felt by patient. If CKD left untreated then progresses towards end stage where the kidney requires dialysis or kidney transplant. Clinically, the CKD stages are identified by GFR test which is invasive, time consuming, and expensive. In few cases, the damaged nephrons remain undetected in GFR test and that results into quick progression of CKD silently which cannot be observed externally. An automatic system is considered for CKD stage detection which is non-invasive, not introduce any discomfort to patient, less time consuming and ease in acquisition of patient data. During the last decade, many computing schemes have been proposed in the literature for identification CKD stages with higher accuracy. However, these methods identify CKD stages in groups to achieve higher

detection accuracy. The detection accuracy is low when the CKD stages are identified individually. Further, the primary reason CKD progression is the gradual death of nephron cells which is a slow process. Therefore, early detection of nephron loss will help the nephrologist to have the first-hand information on the amount of damage to the kidney parts to access the whole kidney health and initiate the treatment procedure to slowdown the CKD progression to avoid further damage to kidney. However, there is no specific study has been made to develop a computing scheme to estimate the nephron loss. In Chapter-3, GLCM based computing method is proposed for classification of CKD stages with improved accuracy. The proposed scheme use *fourteen* contributing features for CKD stage classification. Using the proposed scheme, stage-2 can be identified with 100% accuracy while the other stages with almost 97% accuracy. The proposed scheme has aggregate classification accuracy of 97% which is nearly 15% higher than the similar existing scheme [14]. In Chapter-4, a pattern matching based scheme is proposed to estimate nephron loss in kidney internal parts. It use IR algorithm and SSIM algorithm to capture the similarity value by image comparison of reference image and target image. Using IR algorithm with translation transform, the estimate of relative nephron loss in cortex region of stage-1 to stage-5 is 30% to 34%. The estimate of nephron loss in the medulla region of stage-1 to stage-5 is 46% to 58%. These estimates correlate the clinical observations according to the expert views. In Chapter-5, a unified computing scheme is proposed for identification of CKD stages as well as estimation of nephron loss in different kidney parts. The proposed template based computing scheme is simple and straightforward. It does not require feature extraction and multi-class classifier for stage classification. IR with similarity transform can identify CKD stages with 96% accuracy while the SSIM algorithm can identify CKD stages with 88% accuracy. Finally, in Chapter-6, a computing scheme based on transfer learning model proposed for CKD stage identification using small sized dataset of US CKD images. Simulation results shows that Resnet50 identify individual CKD stage with 97% accuracy and 95% aggregate accuracy. Compared with existing similar works [30], the proposed transfer learning model offers more than 13% higher classification accuracy of CKD stages which is significant.

7 Future Scope

In the future, investigate and explore the effect of CKD progression on pelvis region. This will helps nephrologist to estimate status of pelvis and presence of any anomaly in that region. Also, investigate and explore MedNet (Medical network) TL model, on our data set for estimation of nephron loss and effect of CKD progression within kidney regions cortex, medulla and pelvis.

Publications

Journals

1. Ahmad, Rehan, and Basant K. Mohanty. "Chronic Kidney Disease Stage Identification Using Texture Analysis of Ultrasound Images." *Biomedical Signal Processing and Control*, vol. 69, no. 102695, Aug. 2021, p. 102695, https://doi.org/10.1016/j.bspc.2021.102695

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Under Review

1. Chronic Kidney Disease Stage Identification Using Transfer Learning, Vietnam Journal of Computer Science. Manuscript No- WSPC-VJCS-S-23-00942.

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